Anticipating Future Healthy Food Services in Smart Cities Through Systematic Literature Reviews

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***Abstract*—The onset of the fifth industrial revolution promises to reshape industry-consumer dynamics, particularly impacting the food services sector. This study aims to identify emerging research trends in smart cities, food services, personalized nutrition, and artificial intelligence through a systematic literature review. Natural language processing techniques were employed to extract meaningful terms from titles and abstracts, followed by a modified Non-negative Matrix Factorization (NMF) algorithm to categorize the research into distinct topics. The findings reveal a growing interest in the interdisciplinary field, highlighting smart cities' potential to create seamless connections between consumers, farms, restaurants, and health systems. This connectivity is poised to reduce waste and enable personalized recommendations tailored to individual preferences and health needs. Key factors shaping the future of smart cities include urban mobility, food transportation, dietary monitoring, and waste reduction strategies. Integrating technologies such as blockchain, the internet of things, artificial intelligence, and machine learning is set to enhance efficiency and connectivity, fostering a more sustainable and consumer-centric food ecosystem.**

Keywords-personalized nutrition; food services; smart cities; artificial intelligence; NMF.

I. Introduction

The ongoing Fourth Industrial Revolution is marked by widespread digitalization and automation across industries. It leverages cutting-edge technologies like artificial intelligence (AI), the Internet of Things (IoT), and Big Data to drive innovation and reshape the landscape of various sectors [1], [2].

An important sector that gained from the Industry 4.0 is the food industry and the kitchenware. As other industries, this was associated with an overall increase in innovation, associated with a more automatized, digitalized and data-driven approach of the available food services. Examples range from precision agriculture, efficient supply chain management, personalized nutrition apps and kitchenware with wifi connection to recipe databases in the cloud [3], [4].

Anticipating the advent of the Fifth Industrial Revolution, an unprecedented level of automation, harmonious human–machine collaborations and sustainable practices is to be expected. A cornerstone and defining feature of the future and Industry 5.0 will be smart cities. Due to its primarily urban-based operations and the concepts and characteristics of smart cities, this opens the possibility that the food services sector can be highly impacted. It is likely that customers and consumers will interact in a more engaging and connected way through the offering of more nutritious and efficient meal choices. This can still be combined with sustainability practices, such as optimizing food production and reduce food waste [5], [6].

To gain insight on the multiple dimensions on how this sector can evolve, a search on papers relating smart cities and food services was conducted. However, since this is still an emerging field, only a limited number of papers was available. For that reason, two complementary literature reviews were used to gain more profound results.

This article is structured as follows: first, in Section II, a description of the quantitative literature review methodology is introduced. Then, in Section III, the topics that emerged from this analysis are presented and, finally, in Section IV, the implications of the findings are discussed. These are summarized in the concluding section of the article, Section V.

II. Methodology

This chapter outlines the systematic approach taken for the literature review and topic modeling process. It begins with information gathering, detailing the criteria and sources used for collecting relevant literature. This is followed by data processing, which involves preparing the text data through various preprocessing techniques. The third section discusses the application and modifications of the NMF algorithm. Finally, the chapter concludes with the method used to determine the optimal number of topics.

A. Information Gathering

In order to extract relevant articles, two search engines *PubMed* [7] and *Web of Science* [8] were used. Search keywords were used to unveil research addressing human concerns that could gain from new technologies. In *PubMed*, the search was oriented to research in the health science community, while in *Web of Science* a broaden search was used.

To find the most relevant articles in *PubMed*, MeSH terms (i.e., vocabulary terms used to index and categorize articles in the MEDLINE database) were used [9]. The search looked for articles with the "*nutritional physiological phenomena*" MeSH term, together with requiring the presence of the expression "artificial intelligence" OR "machine learning". This search aimed to unveil research that could use new technologies to improve human healthy eating.

In the *Web of Science* engine, the condition used for the search was the presence of keywords *("smart cities" OR "smart city") AND ("nutrition" OR "food")*. These search keywords were selected so that a statistically significant number of articles could be found linking new technologies (artificial intelligence or machine learning in one case, and smart cities in the other) to food and nutrition.

With these search criteria, 630 articles were found in *PubMed* and 464 in *Web of Science*. For every article, the title, the complete abstract and the year of publication were recorded for data processing analysis, as described next.

B. Data Processing

After collecting the information on the selected articles, the title and the abstract of every article were processed using Natural Language Processing (NLP) techniques. This involved converting every letter to lowercase, removing non letter characters, tokenizing the text (in order to analyze words individually), removing stop-words (the most common English words, such as '*the*', '*or*', '*what*', etc.) and stemming (reducing inflected words to their word stem or root form; for example, the words '*simulation*', '*simulator*' and '*simulate*' can all be reduced to their stem '*simul*').

Another important operation consists in removing words that appear frequently in scientific texts but are not specific to this particular field of interest, such as '*prove*', '*demonstrate*', '*experiment*', etc. In order to do this, 647 articles were collected using *Semantic Scholar* [10] after searching with the keyword "*biotechnology*". The former NLP techniques were also applied on these articles, and the frequency of occurrence for all the words in the two collections of articles (those related to this analysis, and those related to the biotechnology search) was calculated.

Then it was possible to calculate the frequency ratio, FR, as seen in Eq. (1).

$$FR(word) = \frac{Counts_S(word)/Tot_S}{Counts_B(word)/Tot_B} \tag{1}$$

Here, $Counts_X(word)$ represents how many times $word$ appeared in the abstract and title of every article in the nutrition and artificial intelligence and the smart cities and food/nutrition searches (X=S) or on the articles in the biotechnology search (X=B). Tot_X represents the total number of words in the abstract and title of every article on each search. The ratio $FR(word)$ was calculated for every word found on both searches. In the case of the words that did not show up in the biotechnology search, $Counts_B(word)$ was considered to be 1.

With this approach, the 100 words with the highest $FR(word)$ ratio were selected, which allows for pinpointing specific terms that are likely to convey essential information related to the topics of interest.

C. Modified Non-negative Matrix Factorization Algorithm

In order to identify the different thematic areas for each search, a NMF algorithm was used. NMF algorithms find an approximate factorization of an input matrix V into two other non-negative matrices, W and H, such that $V \approx WH$ [11].

In this case, the input matrix V is defined as a binary matrix, where each row is associated with an article, and each column corresponds to one of the top 100 words. The values in the matrix are either 0 or 1, indicating the absence or presence of a word in an article. Being N the number of articles, V is a $N \times 100$ matrix.

The NMF algorithm helps compress the information in V by decomposing it into two smaller matrices, W and H, with dimensions $N \times k$ and $k \times 100$ respectively. Typically, k is no larger than 20, so $N \times k + k \times 100$ is significantly smaller than $N \times 100$.

According to this decomposition, each row in V (representing the words in an article) is expressed as a linear combination of the rows in H. Since the number of rows in H (k) is much smaller than the number of articles (N), this breakdown suggests that articles can be grouped into topics. These topics are characterized by the specific set of words listed in each row of H.

To apply the NMF algorithm it is then necessary to choose the number of topics k. Then the NMF algorithm produces, after an optimization algorithm, the matrices W and H, as represented in Figure 1.

While the entries in W reveal the degree of association between articles and topics, the entries in H indicate the contribution of the words to each topic. Therefore, examining the H matrix reveals connections between words associated with each topic, facilitating the definition of diverse areas where artificial intelligence and smart cities influence nutrition. Meanwhile, from matrix W it possible to understand which articles pertain to specific topics, multiple topics, or none at all.

Given that the number of articles used in these searches is relatively small (in statistical terms), some topics (lines in the H matrix) have one entry (word) dominating all others, as shown in the example in Figure 2. There, the word '*urban*' has a significantly higher value than the others. This would mean that the presence of the word '*urban*' in an article would be enough to associate it to a topic, which is a typical example of over-fitting due to the small number of articles used.

To overcome this problem, an iterative reformulation of the NMF algorithm was developed such that whenever the weight associated with a word in the matrix H represents more than 20% of all the weights in the same topic, the corresponding entry for that word in the input matrix V is decreased by

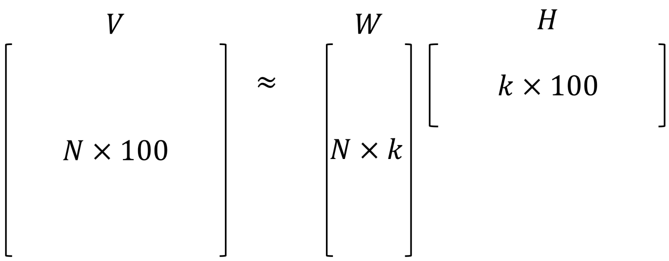

Figure 1: Visual representation of NMF (non-negative matrix factorization) algorithm, where N is the number of articles, k is the number of topics, and 100 is the number of words.

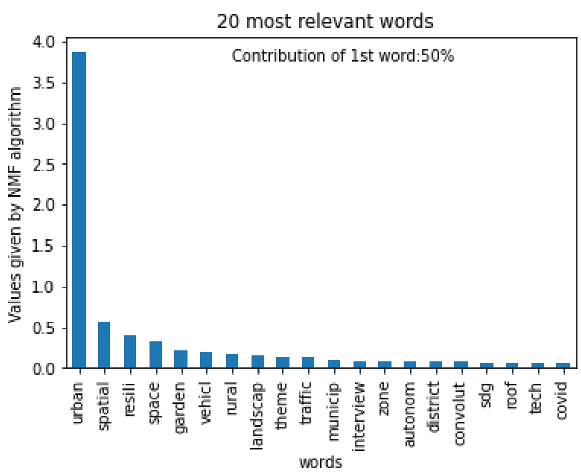

Figure 2: Bar chart representing the 20 words with the highest values for a row of the H matrix of the NMF algorithm before being modified (from the articles in Web of Science searches).

Algorithm 1 Modified NMF

$N \leftarrow$ number of articles
$V \leftarrow (N \times 100)$ binary matrix where $V_{ij} = 1$ if article i contains word j
$W, H \leftarrow$ NMF decomposition of V
$l \leftarrow$ list of the words where $max(H_i)/\sum H_i > 0.2$, for each topic i
while l is not empty **do**
  for every article a **do**
    for every word w in l **do**
      $V_{aw} \leftarrow$ decrease 1%
    end for
  end for
  $W, H \leftarrow$ NMF decomposition of V
  $l \leftarrow$ list of the words where $max(H_i)/\sum H_i > 0.2$, for each topic i
end while

Figure 3: Algorithm of the modified NMF, used to correct overfitting.

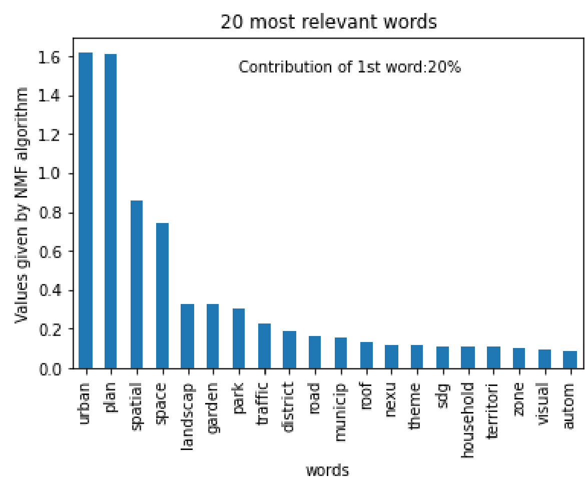

Figure 4: Bar chart representing the 20 words with the highest values for a row of the H matrix of the modified NMF algorithm (from the articles in Web of Science searches).

1%, as detailed in Figure 3. This value was chosen based on preliminary experiments, which indicated that a 1% decrease does not significantly alter the results, but performing this process iteratively is computationally efficient and does not require extensive processing time.

The application of this modified version of the NMF algorithm changed the values of the highest weights in matrix H. A typical example is shown in Figure 4. They show that the decomposition obtained with the modified NMF algorithm requires a larger number of words to define a topic. Furthermore, the semantic consistency of the several words defining each topic shows that this procedure produces much more insightful results.

D. Number of Topics

In order to choose k, the number of topics that each search contained, the squared Frobenius norm was calculated, according to Eq. (2) [12].

$$P_k = ||V - WH||_F^2 = \sum_{ij} |v_{ij} - (WH)_{ij}|^2 \qquad (2)$$

In this equation, W and H have k columns and lines, respectively. The squared Frobenius distance was calculated using the decompositions found with different values of k and using the modified NMF (Figure 3). The results are shown for the two article collections in Figures 5 and 6.

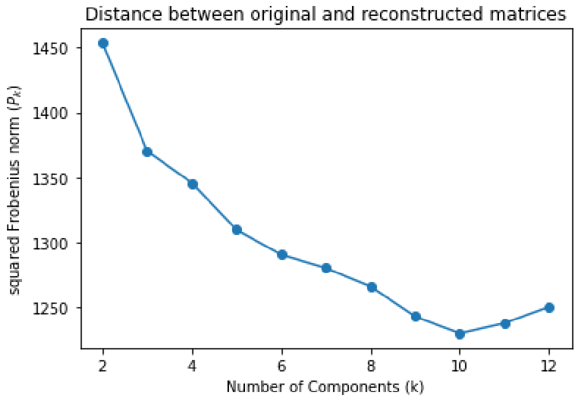

Figure 5: WoS squared Frobenius norm.

From Figure 5, it is possible to observe a minimum for $k = 10$. As such, it was considered that the Web of Science (WoS) research could be grouped into 10 different topics. Likewise, according to Figure 6, $k = 15$ topics were considered optimal for the PubMed search.

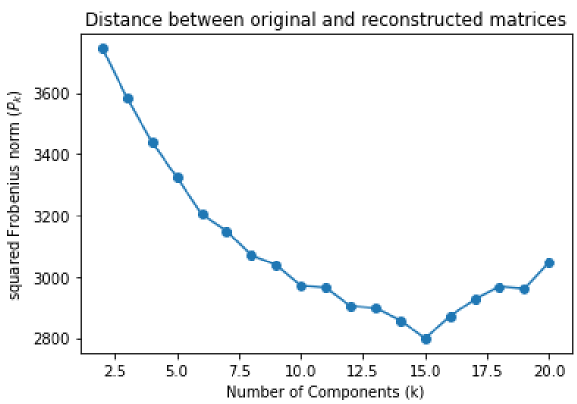

Figure 6: Pubmed squared Frobenius norm.

Given that $k = 15$ represents a significant number of topics, an exploration was conducted to assess whether the increase in the number of topics relatively to the WoS search, was indeed real. This examination aimed to determine if new topics were not generated spuriously. To facilitate this comparison, a distinct nomenclature was adopted for the two sets of topics: numerical labels from 1 to 10 were used for the decomposition with $k = 10$, while capital letters from A to O were employed for $k = 15$. This approach facilitates the clear identification of any correspondence between the two groups of topics.

III. Results

The first result is shown in Table I, where the 15 most common words (i.e., the words with the highest FR) on both searches are listed. These words, although related, are not coincident, showing that the two searches are complementary.

TABLE I: MOST COMMON STEM WORDS FOUND FOR THE TWO SEARCHES, SORTED FROM MOST TO LEAST COMMON

Search	15 Most Common Words
Web of Science: (smart cities or *smart city*) and (*food or nutrition*)	urban, iot, propos, servic, sensor, internet, infrastructur, plan, intellig, spatial, blockchain, mobil, scenario, machin, fresh
PubMed: nutritional psysiological phenomena and (*artificial intelligence* or *machine learning*)	diet, machin, dietari, intak, patient, algorithm, weight, intervent, accuraci, obes, diabet, gut, microbiota, glucos, score

Another interesting result concerns the number of articles published along the time for each search as shown in Fig.7. These results show a clear growth in activity in recent years, on both cases, demonstrating a growing significance of these topics within the scientific community.

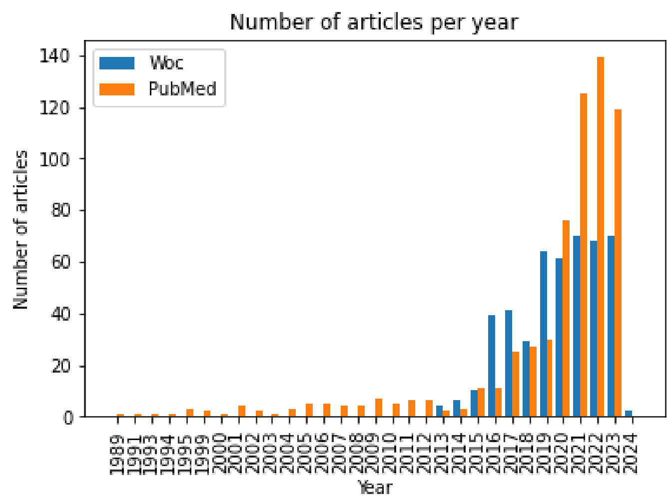

Figure 7: Temporal distribution of the number of articles collected with the two searches.

Moreover, after selecting the most frequent and meaningful 100 words for the analysis, some articles still lacked any of these words in their title or abstract. These articles had to be discarded, as they lacked information for this study. This happened for 23 (out of 464) articles in the WoS search and for 8 (out of 630) in the PubMed search.

Upon implementing the modified NMF algorithm, the rows of matrix H specify the words distinctive to each of the k topics, while matrix W holds the coefficients representing how each article breaks down into these various topics. This information is vital for connecting articles with topics and, as such, a straightforward strategy involves linking each article with the topic exhibiting the highest coefficient in matrix W.

However, choosing the maximum value dismisses the instances where the second, or even third, highest values of the W decomposition are very close to the maximum, meaning that that article has components of more than one topic. This would happen if an article would be at the interface of different topics. In order to define which articles could fall into this situation, it was established that an article i belongs to topic j if it satisfies the condition in Eq. (3):

$$\frac{max(W_i) - W_{i,j}}{max(W_i)} \leq 0.05 \tag{3}$$

Following this criteria, 29 articles were classified as belonging to 2 distinct topics and 1 article was placed into 3 topics in the WoS search. The distribution of the articles in the several topics is shown in Table II. A similar procedure was carried on for the articles in the PubMed search. In this case, the number of articles per topic is shown in Table III for the 622 articles included in the analysis. In this case, 28 articles were associated to 2 different topics simultaneously. These results show that all topics have a significant number of articles, even though some topics have more articles than others.

TABLE II: WOS: NUMBER OF ARTICLES PER TOPIC

	Topic									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Calculation Method	**Number of Articles**									
Max Value	98	47	46	40	34	18	44	50	35	29
Equation 3	103	50	47	42	37	22	45	51	37	38

TABLE III: PUBMED: NUMBER OF ARTICLES PER TOPIC

	Topic														
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**N**	**O**
Calculation Method	**Number of Articles**														
Max Value	114	83	29	28	33	34	48	23	38	23	47	45	30	19	28
Equation 3	114	91	32	29	33	36	51	25	40	24	50	45	31	20	29

In order to confirm that this association procedure indeed makes sense, an individual analysis of articles, as well as of the most important words characterizing each topic (see Figure 8, related to the WoS search, and Figure 10, related to the PubMed search) was undertaken. For example, in the WoS seach, [13] was classified in topics 1, 4 and 6, while based on the maximum value it would only be associated with topic 1. This research explores a method to establish a trusted, decentralized system for food distribution within the framework of a Smart City that integrates IoT, Blockchain technology, and city LoRa network, which is within the frame of topics 1, 4 and 6. In this case, looking at the most important words of topics 1 (servic, infract, rural), 4 (air, store, fresh) and 6 (blockchain, transpar, propos, traceabl) seen in Figure 8, it is possible to understand that this article belongs to topic 1 since it relates to food distribution services, to topic 4 since it is necessary to store the food in order to distribute it and to topic 6 due to the use of blockchain technology.

Another example is of the work of Ragab, Osama, and Ramzy [14], which uses AI and ML to simulate the impact of industries (among which the food industry) in smart cities, being within the framework of both topics 1 and 9. Furthermore, [15] explores the zero-emission strategy and implementation plans of Tokyo city, and its efforts to progress towards achieving net zero emissions by 2050, fitting within topics 1 and 7. Finally, [16] simulated different vegetation cover scenarios, in order to quantify their effects on the microclimate of a mixed-residential-industrial area, relating to both topics 5 and 7.

Similarly, an examination of selected articles belonging to more than one topic, alongside the key terms was made for articles in the Pubmed search. For instance, in [17], which investigates personalized nutrition employing artificial intelligence for patients with irritable bowel syndrome, topics B and I are pertinent. Topic B addresses patient diagnosis and clinical studies, while topic I concerns the utilization of artificial intelligence in such contexts. Similarly, [18] explored the interplay between oxidative damage, the redox status, and metabolic biomarkers during long-term fasting, revealing decreases in blood glucose, insulin, glycated hemoglobin, total cholesterol, low-density lipoprotein, and triglycerides, alongside an increase in the total cholesterol/high-density lipoprotein ratio. These findings align with topics J and O. Furthermore, [19] investigated the interactions between serum free fatty acids and fecal microbiota in obesity, employing a machine learning algorithm to classify subjects by BMI. This study intersects with topics A and F.

Another insightful representation of the distribution of articles per topics is provided in Figures 8, 9 and 10. In these figures, the temporal evolution of the number of articles in each topic is displayed. Furthermore, the most significant words for each topic are also presented, in decreasing order of importance, as mentioned before. These have been obtained from the entries of the H matrix with the highest values. The words considered are those with a weight, in the H matrix, of at least 40% of the word with the highest value for said topic.

To enhance the visualization clarity, a heatmap approach was utilized. For each topic, the year with the highest number of articles appears as deep red, while the year with the lowest count appears as deep blue, with the intensity of color corresponding to the volume of articles. Figures 9 and 10 differ on the k value used in the modified NMF ($k = 10$ and $k = 15$, respectively).

It is noteworthy to observe a global rise in publication activity across nearly all topics. However, due to the relatively small number of articles per topic, drawing further conclusions regarding trends is challenging. Moreover, it is important to acknowledge that although the latest results are recorded up to March 2024, ongoing updates to databases may still be occurring for articles published in 2023.

The heatmaps depicted in Figures 9 and 10 reveal that, at $k = 10$, certain topics appear to encompass articles spanning multiple subject areas. Conversely, with an increase to $k = 15$, new topics emerge (e.g., topics D, E, H, and J), stemming either from the splitting of previous topics or the aggregation of articles from multiple topics.

To support this hypothesis, the fraction P($i|j$), representing the probability of an article coming from topic i ($i \in 1, ..., 10$) for $k = 10$, knowing that was classified under topic j ($j \in A, ..., O$) for $k = 15$, was calculated for all topics. Large P($i|j$) values mean that topic j originated mainly from topic

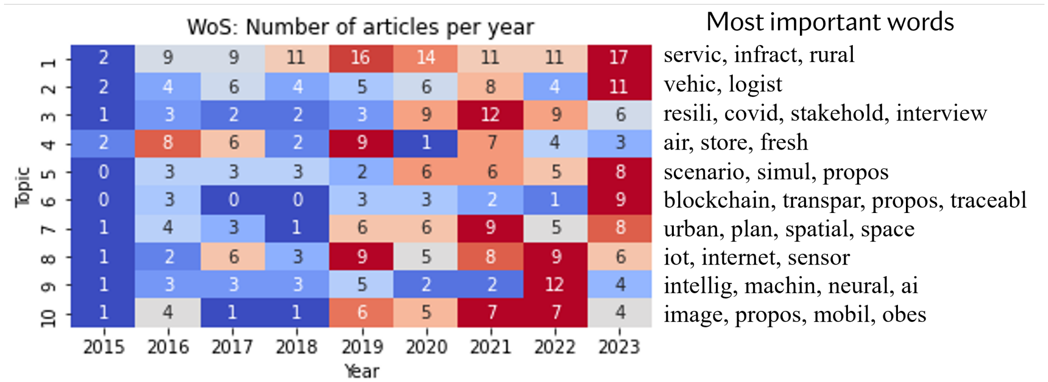

Figure 8: WoS: Temporal evolution of the articles in each topic, as well as the most relevant words.

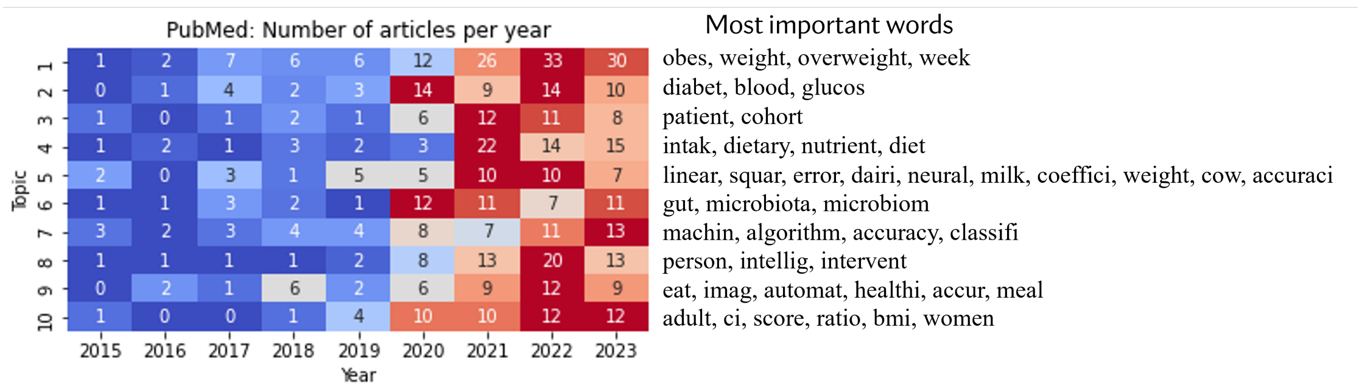

Figure 9: PubMed: Temporal evolution of the articles in each topic (out of 10), as well as the most relevant words.

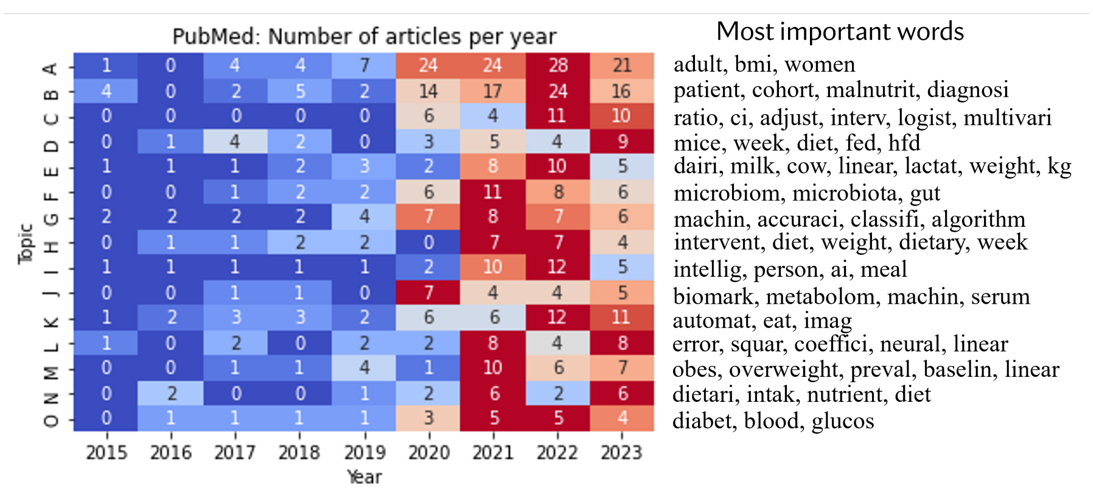

Figure 10: PubMed: Temporal evolution of the articles in each topic (out of 15), as well as the most relevant words.

i. The following results were obtained:

- A originates from $10(31\%)$ and $1(29\%)$
- B originates from $3(45\%)$
- C originates from $10(41\%)$
- D originates from $1(64\%)$
- E originates from $5(66\%)$
- F originates from $6(76\%)$
- G originates from $7(77\%)$
- H originates from $1(47\%)$ and $8(39\%)$
- I originates from $8(78\%)$
- J originates from $6(34\%)$ and $4(26\%)$
- K originates from $9(65\%)$
- L originates from $5(57\%)$
- M originates from $1(86\%)$
- N originates from $4(84\%)$
- O originates from $2(100\%)$

Based on these findings, it is clear that certain topics identified in the analysis with $k = 15$ were already delineated as topics within the $k = 10$ framework. This is particularly notable in instances such as direct transcriptions of O or N. Conversely, some topics identified with $k = 10$ encompassed two distinct themes when scrutinized with $k = 15$. Notably, topics L and E emerged as distinct entities, yet both were belonged to topic 5. This observation confirms that $k = 15$ is a better parameter choice for the number of topics.

Moreover, topics A, D, H, and M originated from a shared theme present in the $k = 10$ analysis, topic 1, which revolves around diet and weight management. However, these topics offer varied perspectives on this overarching theme. Notably, certain nuances within these topics become more pronounced with $k = 15$, as exemplified by the focus on mice experimental models within topic D.

IV. Discussion

In this section, the aim is to examine the ongoing research in the areas regarding the future of the food services sector, including potential benefits to human health, given the emergence of smart cities. As such, some of the articles with less overlap, i.e., with the highest ratio $\max(W_i)/\max(W_i \notin \max(W_i))$, will be further explored. In Tables IV and V, an analysis of the topics emerging from the two searches is outlined. Both searches were coincident on some topics - for example, on applications of artificial intelligence, topic 9 (WoS) and topics G and I (PubMed) - while others provide additional insights. This demonstrates that there is consistency between the methods, which are also complementary.

A thorough analysis of Tables IV and V provides important insights on how food services may evolve in smart cities. For instance, the topic 2 of WoS emphasizes the importance of transporting food to the customers efficiently, reducing transport emissions. Also, topic 5 of WoS shows the importance of planning and mitigating waste in the most sustainable way.

Topic 10 of WoS and topics K and N of PubMed highlight problems related to self-report food intake. For example, children and adolescents are unable to self-report food intake without caregivers [83] and even trained individuals have difficulties in estimating food portions accurately [84]. Solutions with sensors (body sensors, cameras, etc) and artificial intelligence could contribute to monitor and help control food intake, helping to develop better food prescriptions, better disease prediction, and improved prevention strategies.

Also, technologies such as blockchain (WoS topic 6) and internet of things (WoS topic 8), as well as machine learning and artificial intelligence (WoS topic 9 and PubMed topics G and I), will be used for a multitude of applications, from preserving privacy, to improving resource efficiency, image recognition, monitoring and personalizing nutrition.

Moreover, even though just topic E specifically focus on farms, in this case dairy farms, a lot of articles (see WoS topics 6, 8 and 9 in Table IV and topic L in Table V) are related to agriculture, emphasizing the importance of developing a direct connection between farms and consumers, to reduce food insecurity, which is especially relevant for fresh food options (a concern also highlighted in WoS topic 7) and to promote sustainable city expansion and social well-being. Therefore, food services creating a direct link between farms and the consumers' table could be perceived positively.

Furthermore, several diseases or health conditions could benefit from interaction with future food services. For instance, accurate food intake monitoring could help control obesity and diabetes (topic 10 of WoS and topics H, K, M, N and O of PubMed). Also, knowledge awareness for the interplay between nutrition and microbiota (topic F) makes it likely that dietary choices will become increasingly recognized for their pivotal role in intestinal modulation. This understanding underscores the importance of actively selecting ingredients that promote gut health, thereby contributing to the prevention of intestinal disorders and ultimately impacting immune function and overall well-being.

Additionally, regarding the PubMed search, while some topics followed a clear trend, others were more miscellaneous, namely topics C, G, I and L. For example, topic C just consists of articles where the abstract is mostly numerical and presents a lot of results, hence the ratio and confidence interval words. Topics G and I, as mentioned before, are related to machine learning and artificial intelligence in a broad sense, even though most articles have an AI/ML component. Lastly, topic L is related to prediction algorithms across different domains, with all articles sharing a common thread of statistical analysis in their abstracts. Metrics like mean square error and correlation coefficients are commonly reported, highlighting the emphasis on quantitative analysis rather than thematic content within this topic, akin to Topic C.

Furthermore, smart cities and farms can interact regularly to manage storage and delivery efficiently. In the future, food services may interact with consumers, suggesting meals based on information received from them, who are also engaging with health services. Consumers can share health data through tools and sensors, allowing health services to online monitor and recommend nutritional plans. The consumer/patient will have closer access to the healthcare system, thereby

TABLE IV: WEB OF SCIENCE SEARCH: CONTENT TABLE FOR THE TOPICS OBTAINED

Topic	Type of Solution	Example of Problem Addressed
1	Services	Studying the contribution of ecosystem services to farmers' livelihoods [20]
	Sustainable infrastructures	Reviewing the role of smart city innovation for sustainable infrastructure in Bahrain [21]
		Managing thermal energy in a medium aquaponics system, a sustainable alternative food production infrastructure, for biological sustainability, especially during cold weather [22]
2	Urban mobility and transportation of food	Energy efficiency analysis using unmanned aerial vehicle systems and electric scooters in the transport of takeaway food, which is a cheap, fast, and green transportation solution that fits into the zero-emission transport policy of people and goods [23]
		Comprehensive review and analysis of the latest trends in last-mile delivery solutions from both industry and academic perspective [24]
		Mechanism that exploits automated electric vehicles in future smart cities and regions to provide both people transport and fresh food distribution that minimizes empty miles of the vehicles (and thus enhances transport efficiency) while meeting the constraints on passenger transit time and food freshness [25]
3	Urban resilience	Urban resilience capacity and its relations with the economic, social and environmental well-being in smart cities in the state of São Paulo, particularly after the 2008 financial crisis [26]
		Examining government employees' experience and expectation of socioeconomic hardships during the COVID-19 pandemic [27]
4	Storage quality and conditions	Evaluating the physiological and chemical traits of three red and three green baby leaf lettuce during postharvest cold storage [28]
		Characterizing and sensory analyzing the volatile profile of two hybrids of "Radicchio di Chioggia" stored in air or passive modified atmosphere during 12 days of cold storage [29].
		Examining the phenolic profiles and changes in postharvest quality of radicchio leaves when freshly cut and when stored in unsealed bags or in passive modified atmosphere [30].
5	Planning and mitigating waste	Studying whether the installation of food waste disposers in private homes or separate collection and transport of organic waste to biogas plants is a more viable environmental and economic solution, being the latter the most sustainable [31]
	Simulations	Studying the effectiveness behavior change techniques by using computational models that describe human [32]
6	Blockchain and preserving privacy	Blockchain-based innovative framework for privacy-preserving and secure IoT data sharing in a smart city environment [33]
		Novel BIoT-based layered framework using EOSIO for effective food traceability in smart cities [34]
		Literature review about the application of blockchain in the agricultural sector, focusing on food traceability issues [35]
7	Urban planning	Effects of uncontrolled urban development and urban compactness on the quality of life [36]
	Willingness to buy green food products	Studying smart city millennials' willingness to pay a premium toward toxic-free food products [37]
		Identifying the predictors that influence young, educated customers' intention to purchase green food products in India by utilizing the extended theory of planned behavior, which includes elements such as environmental concern, perceived customer effectiveness, willingness to pay a premium, and product availability [38]
8	Implementation of internet of things in smart cities	Internet of Things technology for efficient farming processes, specifically collecting and processing soil nutrients and weather data of crop avocados in an orchard [39]
		Reviewing current literature related to IoT and big data-based food waste management models, algorithms, and technologies with the aim of improving resource efficiency [40]
9	Use of artificial intelligence in food and smart cities	Rice quality evaluation system based on computer vision and machine learning [41]
		Artificial intelligence technology to screen active components of natural products [42]
10	Food image recognition	Integrated image processing framework that extracts numerical nutrition information from the Thai GDA label images [43]
		Computer-aided technical solutions to enhance and improve the accuracy of current measurements of dietary intake [44]
	Medical imaging	Using magnetic resonance imaging processing for fat depot assessments and data analysis [45]
		Using magnetic resonance imaging to examine the differences between metabolically healthy and unhealthy overweight/obesity phenotypes on specific abdominal fat depots and explore whether cardiorespiratory fitness plays a major role in the differences between metabolic phenotypes among overweight/obese children [46]

TABLE V: PUBMED SEARCH: CONTENT TABLE FOR THE TOPICS OBTAINED

Topic	Type of Solution	Example of Problem Addressed
A	Effects of high BMI	Study on plasma folate in pregnant and lactating Chinese women, found that one of the factors contributing to lower folate concentration is higher BMI [47]
	Diets and optimal intakes of food or water in adults.	Prediction of optimal water intake in adults using machine learning [48]
		Evaluating the relationship between the diet quality index of young adults and cardiometabolic risk factors [49]
B	Identifying and/or studying malnutrition in patients	Phase angle as a tool for nutritional monitoring and management in patients with Chron's Disease, usually accompanied by malnutrition [50]
		Personalized nutrition for treating malnutrition in cancer patients using machine learning tools [51]
		Machine learning (multivariate regression and random forest) to predict in-hospital complications in elderly patients diagnosed with malnutrition [52]
C	Numerical results	Predicting hospital length of stay [53]
D	Experiences on mice and the effects of diet on mice	Studying the relationship between the components of cellular magnesium (Mg) home- ostasis and energy metabolism in cardiomyocytes by analysing two groups of mice: one fed a diet with normal Mg content and another fed a diet with low Mg content [54]
		Showing feeding is fragmented and divergent motivations for food consumption or environment exploration compete throughout the feeding process by delineating the behavioral repertoire of mice by developing a machine-learning-assisted behavior tracking system [55]
E	Dairy farms and the feeding of the cows	Using sensors that measure the behavior of cows intended to be included in pasture management [56]
		Real time continuous decision making using big data in dairy farms by using sensors and robotic systems that can collect, integrate, manage and analyze on and off farm data in real time [57]
		MIR spectroscopy to authenticate the milk source at both farm and processor levels for grass fed and non-grass fed milks [58]
F	Gut microbiota	Clarifying the effects of nutrients consumed on the entire gut microbiome by studying gut microbiota differences in identical twins [59]
		Comparing gut microbiota of Cameroonians to people from Philadelphia, finding that the Cameroon diet has more gut parasites, which increases gut microbial diversity [60]
		Finding optimal maturation trajectory of the gut ecosystem through machine learning models, to study the effects of diet on gut microbiome [61]
G	Machine learning models related to food and nutrition	Creating a network-based machine learning platform to identify putative food based cancer beating molecules and a "food map" with the anti-cancer potential of each ingredient [62]
		Using natural language processing and machine learning approaches to categorize food and predict nutrition quality [63]
H	Weight loss and dietary interventions	Artificial intelligence based virtual health assistant [64]
		Machine learning (WEKA decision trees) to predict dietary lapses during weight loss [65]
		Studying the efficiency of a diet-related mobile application based on artificial intelligence by studying the nutritional status of children post-cardiac surgery, giving to part of the study group this application and the other part just a pamphlet. This application was proved efficient [66]
I	Artificial intelligence models	A systematic literature review of precision nutrition [67]
		An educational approach based on intelligent systems and its application in nursing education [68]
J	Metabolomic biomarkers and patterns	Prognostic value of the human milk metabolome and exposome in children with the risk of neurodevelopmental delay (NDD) using a predictive classifier [69]
		Comparing metabolite profiles of habitual diet in serum and urine, using metabolomics for identifying objective dietary biomarkers, and creating serum and urine multiple-metabolite models to predict food intake [70]
K	Diet monitoring	Current technological approaches to monitoring energy intake [71]
		Tool that uses new digital photographing technology to reduce measurement error associated with a food record and the recording burden for respondents by photographing the food before eating [72]
		Reviewing two of the most relevant and recent researches on automatic diet monitoring: one based on image analysis and the other on wearable sensors [73]
L	Prediction algorithms	Machine-learning techniques to predict the daily nutritional needs of pregnant pigs using solely sensor data, according to various configurations of digital farms [74]
		A novel method for predicting the absorption of the drugs from their structures, offering understanding into the structural characteristics linked to drug absorption [75]
M	Predicting Obesity	Using information about the diet and physical activity of the residents of a neighborhood to improve the estimate of neighborhood-level obesity prevalence and help identify the neighborhoods that are more likely to suffer from obesity [76]
		Random Forest and Gradient Boosting Machine models to predict the body mass index of children and, consequently, prevent children obesity [77]
	Identifying diseases in already obese individuals	Machine learning to generate predictive models for knee osteoarthritis incidence in overweight and obese women [78]
N	Nutrient aspect of diet monitoring	Machine learning to explore how reducing the number of questions affects the predicted nutrient values and diet quality score [79]
		Validating the accuracy of an internet-based app against the Nutrition Data System for Research (NDSR), assessing the dietary intake of essential macro-and micro-nutrients for precision nutrition [80]
O	Blood glucose regulation and diabetes management	Artificial intelligence to predict blood glucose level changes resulting from regimen disturbances and recommend regimen changes for compensation for type 1 diabetes [81]
		Comparing machine learning-based prediction models (i.e., Glmnet, RF, XGBoost, LightGBM) to commonly used regression models for prediction of undiagnosed type 2 diabetes mellitus [82]

reducing barriers for health professionals, which can then provide tailored nutritional information, offer practical tools for implementing long-term changes, and monitor progress effectively.

Connecting agriculture and food services in smart cities can create a shorter supply chain, enabling continuous feedback from food services that could influence food supply. This is particularly important, as typical restaurants waste up to 10 percent of their purchased food before it reaches consumers [85]. Smart food services could reduce this waste by optimizing stock and accessing fresh ingredients sent daily from farms, using an automatic stock management system that connects restaurant storage areas with farms, determining when and how much of each ingredient is needed.

Additionally, data on food/nutrient intake is important to inform nutritional policies and monitor individual programs, that can modulate food services. There are several methods to access individual dietary intake and the most frequently used is 24-h recall method. However, there are some difficulties to validate the data, mainly there are no clear evidence that children and adolescents are capable to self-report food intake without caregivers help [83]. There are additional problems that includes difficulties to memorize the 24h food intake and even trained individuals have difficulties to estimate the food portion accurately [84]. So, artificial intelligence will help to quantify food intake with more accuracy. Also, with the development of a customized kitchen capable of precisely controlling food portions, supported by a comprehensive database, which can automatically generate nutritional information including calories, macro-nutrients, and micro-nutrients, accurate monitoring of food intake becomes feasible.

People have the need to connect, and the smart city is a place were everything is connected. Ultimately, connectivity is the key to optimize resources and reduce water and food waste. Through a system of on-demand production, ingredients are not wasted as production, storage, and cooking align with the required quantity. Consequently, this is a scenario where food production, encompassing agriculture, seamlessly integrates with restaurants and households via an automated storage management system. This tool anticipates the need for replenishment and regulates production quantities in real-time.

Finally, automation and connectivity are likely to change human habits in future smart cities. A number of companies are pioneering the development of fully automated food services (see Table VI). These will decrease meal preparation costs and, consequently, it is likely that consumers will adopt these services on a daily basis. It is important to note that the companies listed in Table VI were identified through a separate investigation focused on current market leaders in automated food services, and are not directly related to the systematic literature review. In any case, many of the technologies discussed here will be easily put in play.

TABLE VI: LIST OF AUTOMATED FOOD SERVICE COMPANIES

Name	Location	Cuisine type	Autonomy
Sweetgreen (formerly Spyce)	USA	Bowls	fully
Kitchen Robotics	Florida, USA	Several	partial
Circus (formerly Aitme)	Berlin, Germany	Several	fully
Chef Jasper YPC Tech	Montreal, Canada	Several	fully
Miso Robotics	Pasadena, California	Fast food	partial
Hyper Robotics	Israel	Pizza	fully
Da Vinci Kitchen	Leipzig, Germany	Pasta	fully
Moley Robotics	London, UK	Several	fully
Blendid	Sunnyvale, California	Smoothies	fully
Nala Robotics	Illinois, USA	Several	partial or fully
Dexai Robotics	Boston, USA	Salads	fully
Picnic Pizza	Seattle, USA	Pizza	partial
Café X	San Francisco, USA	Coffee	fully
Roboeatz	Ontario, Canada	Several	fully
Mezli	San Mateo, California, USA	Bowls	fully
I-Robo	Tokyo, Japan	Bowls	partial
Hale	Singapore	Smoothies	fully
Cibotica	Canada	Salads and Bowls	partial
BreadBot	Washington, USA	Bread	fully
Wish&Cook	Portugal	Several	fully
Eatch	Netherlands	Several	fully

V. CONCLUSION

The imminent advent of the fifth industrial revolution promises transformative changes, particularly in the interface between industries and consumers, with profound implications for the food services sector. A systematic literature review was conducted employing a modified Non-negative Matrix Factorization algorithm to quantitatively identify emerging research trends and existing work at the intersection of smart cities, food, nutrition, and artificial intelligence.

The analysis reveals an increasing interest in this interdisciplinary domain within the scientific community, unveiling diverse subtopics for exploration. Through this lens, smart cities emerge as pivotal facilitators of seamless connections among consumers, farms, restaurants, and health systems. Leveraging automated management systems triggered by meal orders, these urban hubs hold promise for waste reduction, optimized environmental logistics, and the customization of consumer preferences, culminating in personalized health recommendations.

This literature review provides insight into how future smart cities, through the establishment of a network made of various participants interconnected with feedback loops, will facilitate the development of innovative food services. Key factors poised to shape the future of food services in smart cities are identified, including urban mobility, transportation logistics, diet monitoring, and waste reduction strategies. The integration of cutting-edge technologies such as blockchain, Internet of Things (IoT), and artificial intelligence and machine learning emerges as indispensable for streamlining processes and fostering interconnectedness.

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